JSESD002: Impacts of Land-use and Land-cover Change on the Hydrology of the Driefontein Wetlands in Zimbabwe

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Abstract

In this study, we hypothesise that the hydrology of the Driefontein Wetlands in Zimbabwe, particularly water quality and groundwater recharge, can be influenced by land-use and land-cover change. We identified and quantified different land-use and land-cover (LULC) categories in and around the Driefontein Wetlands at 10-year intervals for the period 1977 to 2017. This was achieved through the use of Landsat satellite imagery classification in a GIS environment. In this study, Forest and Shrubs, Agriculture and Bare classes increased by 4.04%, 19.24% and 7.05%, respectively, whereas Open Water and Wet Grassland classes decreased during the period by 0.09% and 30.24%, respectively. The study found that there are significant linear relationships between LULC and individual water quality parameters. The statistical significance (p) values: 0.015, 0.046, 0.039, 0.026 and 0.044 at 95% confidence for dissolved oxygen, electrical conductivity, nitrates, pH and phosphates, respectively, show the significance of relationships with land-use and land-cover change. Though these relationships were significant, pH however showed a negative relationship (r = -0.591), while the other water quality parameters exhibited positive relationships. The study also related LULC change to groundwater recharge through running correlation analyses between LULC and recharge. For the years 1976, 1986, 1997, 2007and 2017, the relationships between groundwater and land-use and land-cover had the following r values: 0.389, 0.311, 0.402, 0.223 and 0.057 (Open Water), 0.726, 0.473, 0.246, 0.227 and 0.380 (Forest and Shrubs),

0.410, 0.301, 0.497, 0.253 and 0.308 (Wet Grassland), -0.205, 0.250, -0.011, -0.064 and 0.311 (Agriculture), and -0.092, -0.125, -0.056, -0.221 and 0.392 (Bare). We found that Open Water, Forest and Shrubs and Wet Grasslands classes have positive linear relationships with groundwater recharge, whilst Agriculture and Bare classes have negative linear relationships. The overall conclusion is that water quality and groundwater recharge are highly dependent on LULC classes in the area.

Keywords: groundwater recharge, hydrology, LULC, water quality

Introduction

For sustainable utilisation of environmental and water resources, there is need for proper planning and management (Dwarakish & Ganasri, 2015; Jain & Singh, 2023). Reliance on ground and surface water resources has been increasing due to the increase in population as well as the global economy (Sabale et al., 2023; Scanlon et al., 2023). Among other human interventions, land-use and land-cover change has altered the quality and quantity of both surface and groundwater in natural hydrologic systems (Rahmani & Fattahi, 2024). Human activities such as mining, residential and industrial situations, agricultural activities and logging normally reflect land-use (Tengapoe et al., 2023). Land-cover, on the other hand, is captured in the distribution of vegetation, water, ice and barren land as well as the subsurface, which incorporates groundwater, topography, and so on, all as the earth's land surface attributes (Abegeja, 2024). Land-cover also incorporates those surfaces created by anthropogenic factors/activities such as settlements and leisure exposures (Lambin et al., 2003; Mokhtari et al., 2018; Rawat et al., 2013a).

Land-use/Land-over (LULC) change has become the prime focus in current strategies for the supervision of environmental changes and/or management of natural resources (Rawat et al., 2013a; Tendaupenyu et al., 2017a). LULC change is considered as the single most crucial variable of universal change that affects the ecological systems (Dwarakish & Ganasri, 2015; Rawat et al., 2013b). Human activities create a relationship with natural phenomena through the way they interact, and as such, features of the earth's surface tend to change. To better understand these interactions, change analysis becomes the utmost important phenomenon (Butt et al., 2015; Kelly et al., 2016). LULC modifications have significantly affected the environment through their impacts on water and soil quality, biodiversity, microclimate, groundwater recharge and so on, leading to watershed degradation (Kelly et al., 2016; Tendaupenyu et al., 2017a). Researchers have

explored the connection between hydrological processes and LULC with the aim of trying to understand the natural hydrologic system (Dwarakish & Ganasri, 2015; Kebede et al., 2014; Zhao et al, 2010; Zhu et al., 2012). The spatio-temporal characteristics of wetlands have been incorporated into hydrologic models, that are important in water resource management (Costa et al., 2003; Dwarakish & Ganasri, 2015; Gwak et al., 2014; He et al., 2012; Kilonzo et al., 2014; Suliman, & Jajarmizadeh, 2015).

LULC change, such as urbanisation and deforestation, creates smooth surfaces that allow movement of surface water with ease (Plumb et al., 2017). This reduces the travel time of surface water to rivers, and consequently increases the surface water flow to rivers (Saita, & Berndtsson, 2009). As the dynamics of LULC change become more complicated, a time will come when the use of hydrological resources will no longer be sustainable, and the ecological environment no longer guaranteed, not just locally but regionally (Hoekstra, 2003; Jinno et al., 2009). Some earlier studies conducted used catchment experiments to assess the impact of LULC on hydrology, and varying results were obtained, some even contradicting others (Khare et al., 2014; Mondal et al., 2014). Singh (2015) concluded that there is no relationship between runoff and deforestation. Palamuleni and Annegarn (2011), on the other hand, found that reduction in forest cover increases water yield. Most studies that have documented how hydrological systems are affected by LULC changes have been carried out at a small scale where the cause and effect can be clearly outlined (Habersack et al., 2014). This has led to increased research focusing on impacts of LULC on large basins (Habersack et al., 2014). Although small frequent floods are affected by urbanisation, the rare large floods are not affected in a significant manner (Mondal et al., 2014).

One of the most frequently used methods to understand and quantify the impact of LULC change on hydrology is to implement spatially and physically based models, representing the land surface characteristics of the hydrological system being modelled and all processes being physically estimated (Mondal et al., 2014). However, such a model often requires large datasets, leading to computational problems. Therefore, these models' applicability are limited to mesoscale catchments (Khare et al., 2014; Mondal et al., 2014). As a result, the output of the prediction of the effect of LULC change is highly dependent on the uncertainty of the model implemented.

Groundwater is a resource that significantly affects the social well-being of the human population (Kiptum & Sang, 2017; Marchildon et al., 2016; Wada et al., 2010). The estimated use of groundwater at a global scale lies

between 750-800 km^3, which is double the amount as compared to the past two decades (Kiptum & Sang, 2017; Wada et al., 2010). Groundwater is the main source of water for household use in developing countries (FAO, 2013) due to the fact that it is relatively pure, reliable and also accessible for agricultural use. It has been estimated that 30% of the global population was living in urban areas, which increased to 54%, by 2014, and is projected to increase to 66% by the year 2050 (United Nations, 2014). Such significant demographic increase has led to alterations in urban hydrologic systems (Levison et al., 2016). However, most documented studies about hydrological systems in southern Africa have only focused on surface water, yet there is need to venture into how groundwater is also affected (Bhaskar, 2015). The reduction in groundwater recharge may result in a reduction in the amount of water available for residential and municipal use, as well as threatening the health of wetlands, particularly those that rely on groundwater to sustain wet conditions during dry seasons (Harbor, 2007; Marchildon et al., 2016). Fields such as environmental management and local planning cannot estimate the effects of LULC on hydrology, though interests exist in maintaining groundwater recharge (Bhaduri et al., 2008; Rawat et al., 2015). The objective of this study is to assess the impacts of land-use and land-cover on the hydrology of Driefontein Wetlands in Zimbabwe.

Study Area

The Driefontein Wetlands was selected as a case study because it has been labelled as one of the wetlands of international importance in Zimbabwe (Marambanyika et al., 2017). Located between Felixburg, Chivhu and Mvuma, the Driefontein Wetlands (approximately 201 194 ha) encroaches into three provinces in central Zimbabwe, namely, Mashonaland East, Masvingo and Midlands. The coordinates of its centroid are 30^o 47” 00’ E, 19^o 16” 00’ S (Fig. 1). With a gentle undulation, the study site is a plateau that lies between 1,300 and 1,600 m above sea level. The geography in the Driefontein Wetlands is portrayed by extents of clear, wet grasslands, seasonal riverine wetlands, and patches of woodlands which divide the grasslands. Its characteristic location on Zimbabwe’s central plateau gives it a flat terrain which results in the formation of veils due to the collection of water in depressions, soaks and seeps (Fakarayi et al., 2015).

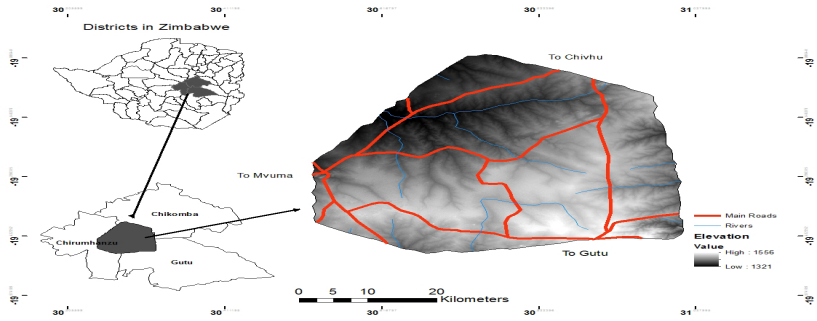


Figure 1: Map of the study area

Methodology

Data Acquisition

The Driefontein Wetlands is covered by 2 Landsat satellite scenes, namely, 170/73 and 169/73 for the Landsat TM, ETM+ OLI-TIRS satellite missions, and scene 182/73 for the Landsat MSS satellite mission. The United States Geological Survey (USGS) Global Visualisation Viewer (GLOVIS) was used to download the respective satellite scenes for the years 1976, 1986, 1997, 2007 and 2017. Table 1 shows the sensor, scene, image acquisition dates, resolution (spatial) and the bands used for visualisation and change analysis.

Table 1: LULC classification imagery description

Year	Sensor	Scene	Date of Acquisition	Resolution (m)	Bands
1976	Landsat 2 MSS	182,73	22 June	60	3, 2, 1
1986	Landsat 5 MSS	169,73	20 June	60	3, 2, 1
		170,73	14 July	60	3, 2, 1
1997	Landsat 5 TM	169,73	23 July	30	5, 4, 3
		170,73	25 July	30	5, 4, 3
2007	Landsat 5 TM	169,73	28 June	30	5, 4, 3
		170,73	21 June	30	5, 4, 3
2017	Landsat 8 OLI-TIRS	169,73	12 July	30	6, 5, 4
		170,73	19 July	30	6, 5, 4

False colour composites were used to differentiate vegetation types, define water surfaces, and observe land interfaces and soils. Bands '6, 5, 4' and '5, 4, 3' represent the Short-wave Infrared, Near Infrared and Red bands for the Landsat 8 OLI-TIRS and Landsat 5 TM, respectively. For Landsat 2 MSS and Landsat 5 MSS, bands 3, 2, 1 were used, which represent the

Near Infrared, Red and Green bands, respectively. The false colour composite image enhancement is very useful for the differentiation of LULC classes (Tendaupenyu et al., 2017b). The selected image acquisition dates were as a result of availability and the images were cloud free.

Data Preprocessing

Before image classification was performed, the Landsat images had to be mosaicked to create a single image that would cover the entire study area for each year that was being looked at. The World Geodetic System 1984 (WGS84) datum was used to geo-reference the images to the Universal Transverse Mercator zone 36 south (UTM 36S) projection.

LULC Changes

For a favourable representation of the study region, training samples were distributed throughout the study region for every land-use and land-cover class that was selected (Tendaupenyu et al., 2017b). The calculation statistics require a minimum of 500 pixels for the result to be meaningful (Tendaupenyu et al., 2017b; Mather & Tso, 2009), and such were selected for each LULC class. Table 2 shows the selected classes used for the representation of the landscape. The Interactive Supervised Maximum likelihood classification method was used to classify the images for the five years (1976, 1986, 1997, 2007, 2017) ArcGIS, ArcMap software version 10.3.1. The Maximum likelihood classification computes the probability that a pixel belongs to a particular class, based on the training samples given to the software (Lucas et al., 2002; Tendaupenyu et al., 2017b). The area covering the Driefontein Wetlands was extracted from the classified images, showing the defined classes as follows: Open Water, Wet Grassland, Forest and Shrubs, Agriculture and Bare (Table 2).

Table 2: Description of LULC classes used in the study

Class	Description
Open Water	Areas with open water bodies, such as dams and rivers
Wet Grassland	Areas covered by grasslands that are mostly wet throughout the year
Forest and Shrubs	Areas covered by grown trees and shrubby plants
Agriculture	Areas covered with agricultural activities like cropping etc.
Bare	Areas with no observed cover, unused land and degraded land

Classification Accuracy Assessment

A hand-held Global Positioning System receiver was used in January 2018 to collect a total of 123 ground control points that were to be used for the validation of image classification of the study area for the 2017 image.

Google Earth was also used to collect additional verification points to classify the 2017 image. Ground truthing data for the preceding years (2007, 1997) was obtained from Google Earth imagery due to its high-resolution sensors. These were for the dates that the 2007 and 1997 Landsat images were also acquired. The remaining two images' (1986, 1976) assessment was based on aerial photographs of the region under study. The confusion matrix (error matrix) was implemented in a GIS environment to compute a Kappa statistic, and assess the overall accuracy of the satellite images, respectively.

Relationship between Water Quality and LULC

Data acquisition and sampling

Historical data on water quality assessments was used in this study and was sourced from the Environmental Management Agency (EMA) for the period 2003-2017. Water quality samples of 15 sites were also collected from the field and tested in the laboratory for verification of the historical water quality data. Stratified random sampling was used to select the sampling sites, where the area was divided into water surfaces and land surfaces. Random points were then selected from the two groups, with six points selected from the water surfaces and nine sites selected from the land surfaces strata. This data was used to determine if there is any relationship between water quality and the changes in LULC. Fig. 2 shows the distribution of the sampling points within the study area.

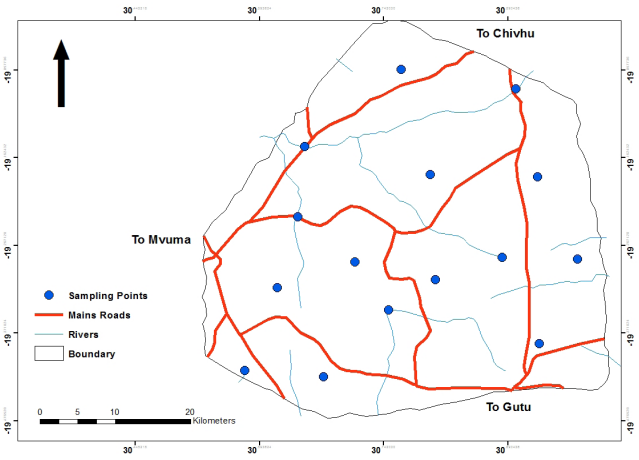


Figure 2: Sampling points for field data collection

Relating water quality to LULC

Before any statistical analyses were conducted, the data was first tested for normality (to check if the data follows a normal distribution or not) using the Shapiro-Wilk test at 95% confidence interval. This test was to determine if parametric or non-parametric tests were to be used in the analysis, and was selected on the basis that it is the most suitable for small samples, that is, samples smaller than 50. Statistical analyses were done to determine the relationship between water quality and changes in LULC. These tests were based on the output of the Shapiro-Wilk test, that is, whether or not the data is normally distributed. The degree of association of two variables was determined using Pearson Correlation Analysis (product-moment correlation coefficient), whether the relationship is positive linear or negative linear. This was done under the assumption that LULC determines the state of the different water parameters, as such making water parameters dependent on LULC. LULC was therefore treated as the independent variable, and the different water quality parameters as the dependent variables. The Statistical Package for the Social Sciences (SPSS) was used to calculate the Pearson coefficient. The Pearson coefficient r, and the sample n size, was used to determine a critical value at the 95% confidence interval. SPSS determined a square of the Pearson correlation coefficient r^2, which is the coefficient of determination. In principle, the coefficient of determination is calculated using explained variation and total variation. It explains the strength of the relationship between variables, and is a measure of the proportion of variance in water quality that is explained by LULC change. As the coefficient of determination approaches 1.0, it means that there is a strong relationship between water quality and LULC change.

Relationship between Groundwater Recharge and LULC

Data acquisition

The WetSpass model extension for ArcView GIS was used for the computation of groundwater recharge. The inputs required for this model are LULC classes; precipitation; potential evapotranspiration; windspeed; the average, minimum and maximum temperature; groundwater levels; soil map and topography map. LULC classes used were those of the classified images for the years 1976, 1986, 1997, 2007 and 2017. The following classes were used for the study: Open Water, Forest and Shrubs, Wet Grassland, Agriculture and, lastly, Bare. Precipitation data used in the study was obtained from the CHIRPS rainfall database for the years; 1986, 1997, 2007 and 2017 since CHIRPS data has good spatial and temporal resolution. Rainfall data for

the year 1976 was obtained from the Masvingo Meteorological Station. Wind speed and temperature data used in the study were obtained from the WorldClim climate variables database. MODIS/Terra Evapotranspiration (MOD16 ET), 8-day global 500m data was used for evapotranspiration data. Groundwater level monitoring data was used to monitor the groundwater level in the province.

Calculating groundwater recharge

Using the 15 sampling sites that were used for water sampling, groundwater recharge was computed for the respective sites using the WetSpass model. The WetSpass model is a code based on the water balance equation, which is computed as follows:

$$R = P - Q - ET - S \qquad \textit{equation 1}$$

where R is the groundwater recharge, P is the rainfall, Q is the surface runoff, ET is the evapotranspiration, and S is the change in soil water storage. All terms of the water balance equation should have the same unit, usually given as a rate (unit depth per unit time) such as mm/month or mm/year. It should be noted that S approaches zero if calculations are made on an annual basis. The equation was later modified to incorporate LULC classes, windspeed, temperature, groundwater levels, soil type and slope (degrees). The code is implemented as a standalone App based on the Visual Basic (VB) programming language or as a file extension in ArcView GIS. The extension for calculation of groundwater recharge in ArcView GIS was used in this study.

Relating groundwater recharge to LULC

Groundwater recharge was computed for each sampling point in the study area and the results extracted. The recharge data was imported to SPSS statistical software to compute a normality test to check whether they follow a normal distribution before any correlation/regression analyses were conducted. Due to the sample size of the data, the Shapiro-Wilk test was used to test for the distribution of the data. This test was to determine if parametric or non-parametric tests were to be used in the analysis and was regarded as the most appropriate.

Results

LULC Change Patterns for 1976-2017

The Land satellite images for 1976, 1986, 1997, 2007 and 2017 were reclassified into the following classes: Open Water, Forest and Shrubs, Wet Grassland, Agriculture and Bare areas (Fig. 3). The LULC change statistics for the Driefontein Wetlands for the period 1976-2017 are shown in Table 3. In the year 1976, Wet Grasslands occupied approximately 77% of the total area of the Driefontein Wetlands, while Open Water, Forest and Shrubs, Agriculture and Bare areas 0.18%, 18.3%, 1.6% and 2.2%, respectively (Table 3). During the period 1976-2017, three LULC classes, namely, Forest and Shrubs, Agriculture and Bare increased in area from 369.0916, 31.752 and 44.2872 km^2, to 450.3807, 419.319 and 186.2064 km^2, respectively. The satellite images for the Driefontein Wetlands were analysed and the change in the area covered by each LULC class obtained (Fig 3). Overall, from the year 1976 to the year 2017, LULC classes in the Driefontein Grasslands, namely, Open Water, Forest and Shrubs, Wet Grassland, Agriculture and Bare experienced a -0.08519, 4.035651, -30.2371, 19.24101, and 7.045669% change, respectively as shown in Fig. 4 (on page 36).

Image Classification Accuracy Assessment

Change analysis in LULC for the Driefontein Wetlands was done for the years 1976, 1986, 1997, 2007 and 2017, the times when satellite images were available and there was no cloud cover. The classification accuracy of the images was verified using the Kappa statistic, overall accuracy, producer's accuracy and user's accuracy, as shown in Fig. 3. For the years 1976, 1986, 1997, 2007 and 2017, the Kappa Statistics were 0.82, 0.73, 0.71, 0.82 and 0.72, respectively. The overall accuracy was 85.3%, 75.2%, 72.5%, 85.3% and 73.3%, for the years 1976, 1986, 1997, 2007 and 2017. The computed Kappa Statistics for the classified images showed substantial agreement and, as such, were suitable for LULC change analysis in the Driefontein Wetlands (Tendaupenyu et al., 2017b).

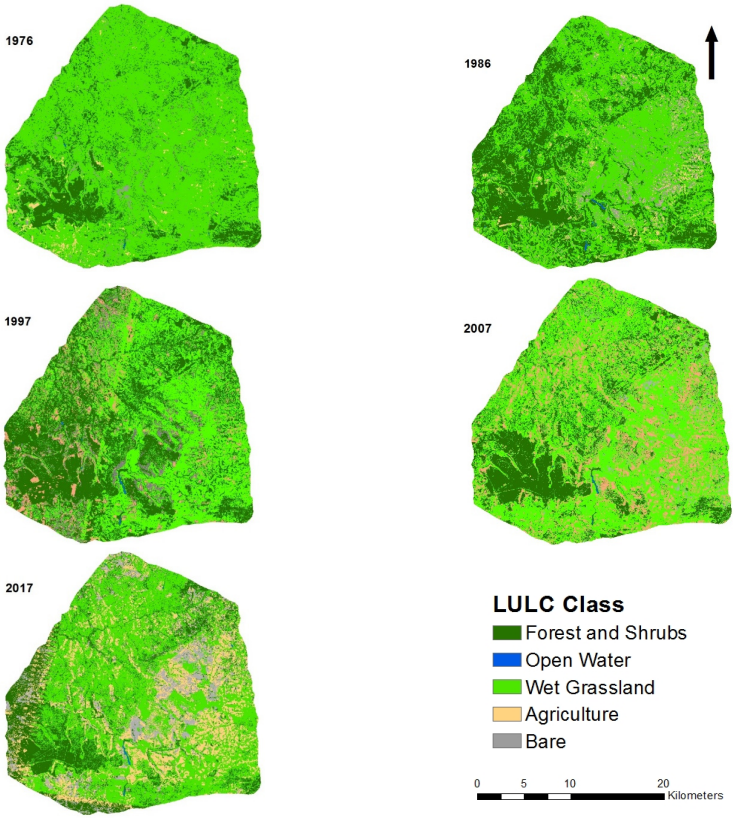


Figure 3: LULC classes for the Driefontein Wetlands for the years 1976, 1986, 1997, 2007 and 2017

Table 3: LULC change area statistics for the period 1976-2017 in the Driefontein Grasslands

	1976		1986		1997		2007		2017		1976 - 2017	
LULC	km2	%	km2	%	km2	%	km2	%	km2	%	km2	%
Open Water	**3.6348**	0.180452	**3.6828**	0.182835	**1.9431**	0.096466	**0.9747**	0.04839	**1.9188**	0.09526	**-1.716**	-0.08519
Forest and Shrubs	**369.0916**	18.32378	**704.0844**	34.95472	**815.4963**	40.48583	**500.3631**	24.84084	**450.3807**	22.35944	**81.2891**	4.035651
Wet Grassland	**1565.51**	77.72075	**1148.299**	57.00805	**896.3712**	44.50092	**1101.468**	54.68307	**956.4509**	47.48361	**-609.06**	-30.2371
Agriculture	**31.752**	1.576348	**75.4056**	3.743559	**132.392**	6.572685	**339.4998**	16.85468	**419.319**	20.81736	**387.567**	19.24101
Bare	**44.2872**	2.198666	**82.8036**	4.110838	**168.0732**	8.344101	**71.9703**	3.573011	**186.2064**	9.244335	**141.9192**	7.045669
Total	**2014.276**	100	**2014.276**	100	**2014.276**	100	**2014.276**	100	**2014.276**	100		

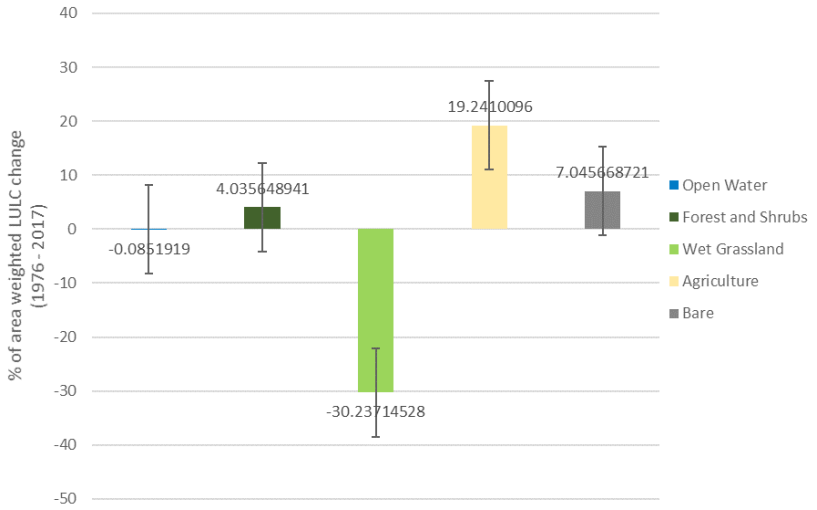


Figure 4: Area weighted LULC change for the period 1976-2017 in the Driefontein Wetlands

Results of Water Quality Data Normality Test

The test for normality for the water quality parameters (dissolved oxygen, electrical conductivity, nitrates, pH and phosphorus) was done in SPSS. Based on the test statistics, the data is all normally distributed (Table 4). The significance values of the normal distribution for dissolved oxygen, electrical conductivity, nitrates, pH and phosphates were <0.01, 0.040, 0.002, 0.026 and 0.011, respectively. Although all the data was normally distributed, the analysis only found statistically significant results for electrical conductivity, pH, and nitrates. The normality for dissolved oxygen and nitrates was found insignificant by the *p* value at 95% confidence interval. Table 4 shows the results of the test, and we have observed that the data followed a normal distribution, which allowed the application of parametric tests for the analysis of the data.

Relating LULC to Water Quality

The individual LULC change patterns that were identified were tested to check whether there is a significant relationship between the change patterns and water quality. Table 5 (on page 38) shows the output results from the Pearson's correlation coefficient. Table 6 (on page 38) shows the overall

strength of the relationship between water quality parameters and LULC change. Overall, it can be observed that LULC can influence changes in water quality, be it positively or negatively. Parameters like dissolved oxygen and phosphates with r^2 values of 0.586 and 0.671, respectively, show that LULC change can influence changes in these parameters by 58.6% and 67.1%. LULC has an influence on electrical conductivity, nitrates and pH of less than 50% as indicated by the r^2 values of 0.276, 0.325 and 0.350, respectively. Using the Pearson's coefficient (Table 6), Open Water showed a positive correlation with dissolved oxygen and pH of 0.055 and 0.226, respectively, whilst keeping a negative correlation with electrical conductivity, nitrates and phosphates of -0.308, -0.204 and -0.105, respectively.

This showed that as the amount of open water increased, the dissolved oxygen and pH also increased, whist electrical conductivity, nitrates and phosphates decreased. Forest and Shrubs was observed to have positive relationship with dissolved oxygen and electrical conductivity, and negative relationships with nitrates, phosphates and pH with coefficient values of 0.607, 0.261, -0.347, -0.282 and -0.583, respectively. The same characteristics as those of Forest and Shrubs were also observed with Wet Grasslands, and the *r* values for the parameters as mentioned above were 0.004, 0.315, -0.190, -0.058 and -0.706, respectively. The above two LULC classes (Forest and Shrubs, Wet Grassland) show that dissolved oxygen and electrical conductivity increase when they increase in size, whereas, pH, nitrates and phosphates only increase when the classes decrease. Agriculture is seen to have a negative relationship with pH and dissolved oxygen, while maintaining a positive relationship with the rest of the parameters, as shown by the following values: -0.205, 0.250, 0.011, -0.064 and 0.311 for dissolved oxygen, electrical conductivity, nitrates, pH and phosphates, respectively. Bare land only exhibited a positive correlation with one water quality parameter (electrical conductivity), and negative relationships with the rest of the parameters, that is, dissolved oxygen, nitrates, pH and phosphates.

Table 4: Shapiro-Wilk test for normality of the water quality parameters

Parameter	**Shapiro-Wilk test**		
	Df	**Statistic**	***P***
Dissolved Oxygen	16	0.559	<0.01
Electrical Conductivity	16	0.892	0.040
Nitrates	16	0.789	0.002
pH	16	0.933	0.026
Phosphates	16	0.951	0.011

Table 5: Pearson's correlation coefficient* r *between changes in LULC and changes in water quality for the period 2003-2017

LULC		**Dissolved Oxygen**	**Electrical Conductivity**	**Nitrates**	**pH**	**Phosphates**
Open Water	***r***	0.055	-0308	-0.204	0.226	-0.105
	p	**0.045**	0.264	0.046	0.017	**<0.01**
Forest and Shrubs	***r***	0.607	0.261	-0.347	-0.282	-0.583
	p	0.017	0.038	0.026	0.038	0.023
Wet Grassland	***r***	0.004	0.015	-0.190	-0.058	-0.706
	p	**0.028**	0.253	0.049	**0.037**	**0.048**
Agriculture	***r***	-0.205	0.250	0.011	-0.064	0.311
	p	0.033	0.038	**0.048**	**0.022**	0.029
Bare	***r***	-0.092	0.255	-0.256	-0.069	-0.229
	p	**0.043**	0.039	0.036	**0.016**	0.011

Table 6: Overall correlation between LULC and individual water quality parameters

Parameter	***R***	r^2	***P***
Dissolved Oxygen	0.766	0.586	0.015
Electrical Conductivity	0.526	0.276	0.046
Nitrates	0.570	0.325	0.039
pH	-0.591	0.350	0.026
Phosphates	0.819	0.671	0.044

Groundwater Recharge

Overall, groundwater recharge computed for the years 1976, 1986, 1997, 2007 and 2017 in each sampling site showed a decrease in recharge during those years. Table 7 shows that the spatial and temporal variation of groundwater recharge increased from 158.6 mm to 162.3 mm from 1976 to 1986. There was also a slight decrease from 1986 to 1997, with estimated recharge values of 162.3 and 156.9 mm, respectively. This showed a decrease of approximately 5.4 mm. A sharp decrease was estimated between the years 1997 and 2007, which showed 2007 recording 138.3, a decrease of 18.6, from the previous decade. This is also the highest estimated decrease in the five decades, that is, 1976, 1986, 1997, 2007 and 2017. Groundwater recharge

estimate increased from the year 2007 at 138.3, to the year 2017 at 149.7. Overall, groundwater recharge decreased during the five-decade period during which the estimations were made. This is shown by the value 158.6 in 1976, and the values 149.7 in 2017.

Table 7: Estimated annual recharge values for the 15 sampling sites from 1976-2017

Site	**Year**				
	1976	**1986**	**1997**	**2007**	**2017**
1	134	135	205	115	182
2	176	184	203	197	161
3	165	131	116	106	140
4	110	183	107	105	157
5	161	152	149	123	150
6	154	194	137	163	173
7	143	104	168	111	116
8	176	143	145	105	202
9	144	156	161	181	124
10	156	183	139	169	154
11	188	150	189	99	106
12	206	139	193	120	191
13	205	196	144	189	122
14	163	188	172	155	99
15	98	196	126	137	168
Average	**158.6**	**162.3**	**156.9**	**138.3**	**149.7**

Recharge Data Normality Test

The significance values of the normal distribution for the years 1976, 1986, 1997, 2007 and 2017 were 0.039, 0.021, <0.01, 0.032 and 0.041, respectively. Based on these values, the normality of the 1997 recharge values is not significant, whilst the recharge for all the other years significantly follows a normal distribution. Table 9 (on page 41) shows the results of the test, and we have observed that the data followed a normal distribution, which allowed the application of parametric tests for the analysis of the data.

Table 8: Normality test for the yearly groundwater recharge data

Year	Shapiro-Wilk test		
	Df	**Statistic**	***P***
1976	16	0.676	0.039
1986	16	0.625	0.021
1997	16	0.705	<0.01
2007	16	0.911	0.032
2017	16	0.908	0.041

Relating LULC to Groundwater Recharge

The relationship between LULC and groundwater recharge was computed for the individual LULC classes and the recharge for the years was estimated. Open Water showed a significant positive linear relationship to groundwater recharge in the years 1976, 1986, 1997, 2007 and 2017, as shown by the *p* values 0.043, 0.032, 0.023, 0.019 and 0.041, respectively. Forest and Shrubs, Agriculture and Wet Grasslands also had significantly positive linear relationships to groundwater recharge in most of the years, though in 2007, Agriculture had a significantly negative linear relationship with a significance value (*p*) of 0.028.

These results imply that LULC classes such as Open Water, Forest and Shrubs, Wet Grasslands and Agriculture increase recharge to the groundwater storage, as such an increase in any of those cover classes is most likely to increase groundwater recharge. However, the Bare land-cover class, though with a positive relationship in 2017 (*p*-value = 0.041), has shown a significant negative linear relationship with groundwater recharge. The results of significance tests for the years 1976, 1986, 1997 and 2007 are 0.042, 0.039, 0.0237 and <0.01, respectively. These results imply that a positive change in bare land-cover would effect a negative change to groundwater recharge in the area.

Table 9: Pearson's correlation coefficient for LULC and groundwater recharge

LULC		**1976**	**1986**	**1997**	**2007**	**2017**
Open Water	***r***	0.389	0.311	0.402	0.223	0.057
	p	0.043	0.032	0.023	0.019	0.041
	n	5	5	6	6	6
Forest and Shrubs	***r***	0.726	0.473	0.246	0.227	0.380
	p	0.017	0.033	0.047	<0.01	0.023
	n	2	4	3	2	1
Wet Grassland	***r***	0.410	0.301	0.497	0.253	0.308
	p	0.788	0.058	0.563	0.837	0.988
	n	5	2	0	1	0
Agriculture	***r***	-0.205	0.250	-0.011	-0.064	0.311
	p	0.043	0.036	0.048	0.028	0.029
	n	2	3	4	5	7
Bare	***r***	-0.092	-0.125	-0.056	-0.221	0.392
	p	0.042	0.039	0.0237	<0.01	0.041
	n	1	1	2	1	1

Note: n is the number of the sampling sites that the particular LULC class occupied in that year.

Discussion

LULC in the Driefontein Wetlands during the period 1976 and 2017 showed a decrease in Open Water and Wet Grasslands by 0.08519 and 30.2371%, respectively, while concentrations of nitrates and phosphates in the water increased during the same period. This loss in Open Water sources and Wet Grasslands can be attributed to the clearing of grassy areas to make way for

agricultural activities, as evidenced by an increase in land for agriculture by 19.241%. Such findings support the findings by Tendaupenyu et al. (2017) that agricultural activities tend to decrease grasslands and water bodies. The highest increase in agriculture was recorded during the period 1997-2007, the same period that Zimbabwe had the fast track land reform programme (Kibena et al., 2013). Groundwater recharge recorded the highest decrease, with a loss of 18.6 mm from the previous decade. The use of machinery during farming activities can result in compression of the soil, filling up pores that allow water to sink into the ground. This is signified by the negative relationship between recharge and agriculture in 2007, p value of 0.028.

Beverly and Hocking (2012) also had the same findings in a study on the trends of groundwater in response to land-use. The same period that agricultural coverage and bareland increased coincides with the increase in phosphates and nitrates in the water available in the study area by almost more than 100%. Agricultural practices such as crop farming tend to introduce nutrients into the soil in the form of fertilisers, whilst bare surfaces create a passage for washing away of these nutrients into nearby water bodies, thereby increasing the concentration of these nutrients in water bodies. There is also a negative relationship between dissolved oxygen and Agriculture. Enrichment of water bodies with nutrients leads to the stimulation of the growth of aquatic plant life, which results in the depletion of oxygen in water bodies. These findings also cohere with the findings of Kibena et al. (2013) and Jamil et al. (2014). Changes in Agriculture indicate a significant negative linear relationship (p = 0.022) with pH. The highest increase in Agriculture (1997-2007) coincides with a decrease in pH, which could explain the introduction of substances into water bodies which increase the acidity of the water.

The area classified as Forest and Shrubs also increased during the period of the study by 4.036%. This can be a result of national reforestation programmes in communal lands as a response to massive deforestation rates experienced in the country during the same period (Tendaupenyu et al., 2017b). The strong negative relationship between Forest and Shrubs and nitrates and phosphates, with significant values of 0.026 and 0.023, respectively, could be attributed to the uptake of such nutrients by plant species, leading to the decrease in the water sources (Salman et al., 2018). Forests and Shrubs have a strong positive relationship with recharge, as evidenced by significance values of 0.017, 0.033, 0.047, <0.01 and 0.023 for the years 1976, 1986, 1997, 2007 and 2017, respectively. Vegetation acts as a barrier to surface runoff, a function which gives more time for water to sink into the ground and, consequently, increase groundwater recharge.

Surface coverages like Open Water, with the ability to retain large

amounts of water, are bound to increase the infiltration and percolation of water into the sub-surface (Levison et al., 2016). The findings of this study go hand in hand with the findings of Levison et al. (2016), as supported by p values < 0.05 at the 95% confidence interval. The presence of fresh water neutralises saline substances in water, reducing the electrical conductivity of the water. Phosphates and nitrates also decrease with an increase in fresh water. Studies by Jamil et al. (2014) Marambanyika et al. (2017) cohere with these findings.

Conclusions

In this study three conclusions were drawn:

a) The largest change in LULC was seen in Wet Grasslands, whilst the least change was in Open Water. Forest and Shrubs, Agriculture and Bare classes increased by 4.04%, 19.24% and 7.05%, respectively, whereas Open Water and Wet Grassland decreased during the period by 0.09% and 30.24%, respectively.

b) Water quality parameters are highly dependent on LULC classes, a change in LULC to trigger changes in water quality parameters such as pH, dissolved oxygen, electrical conductivity, nitrates and phosphates. The significance of the relationship between LULC and water quality shows that LULC highly influences water quality.

c) Changes in LULC influenced changes in groundwater recharge, with increases in Bare land decreasing recharge, and increases in Forest and Shrubs increasing groundwater recharge. From the findings of the study, LULC is highly related to groundwater recharge as it influences the rate of recharge.

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Appendix 1: Image classification accuracy assessment

LULC		Reference Data						
		Open Water	Wet Grassland	Forest and Shrubs	Agriculture	Bare	Total	User's Accuracy (%)
Accuracy assessment of the Landsat 2 MSS 1976								
Classification Data	Open Water	25	3	0	7	0	35	71.4
	Wet Grassland	1	53	1	0	0	55	96.4
	Forest and Shrubs	0	2	33	6	0	41	80.5
	Agriculture	2		0	24	1	27	88.9
	Bare	0	0	5	0	27	32	84.4
Total		28	58	39	37	28	190	
Producer's Accuracy (%)		89.3	91.4	84.6	64.9	96.4		
Overall Classification = 85.3%, Kappa Coefficient = 0.82								
Accuracy assessment of the Landsat 5 MSS 1986								
Classification Data	Open Water	33	6	3	1	4	47	70.2
	Wet Grassland	1	61	7	1	1	71	85.9
	Forest and Shrubs	4	7	33	0	0	44	75
	Agriculture	5	4	0	29	3	41	70.7
	Bare	8	0	2	3	26	39	66.7
Total		51	78	45	34	34	242	
Producer's Accuracy (%)		64.7	78.2	73.3	85.3	76.5		
Overall Classification = 75.2%, Kappa Coefficient = 0.73								
Accuracy assessment of the Landsat 5 TM 1997								
Classification Data	Open Water	22	5	4	8	1	40	55
	Wet Grassland	4	54	0	4	7	69	78.3
	Forest and Shrubs	1	1	47	3	11	63	74.6
	Agriculture	3	7	2	39	0	51	76.5
	Bare	6	1	0	3	25	35	71.4
Total		36	68	53	57	44	258	
Producer's Accuracy (%)		61.1	79.4	88.7	68.4	56.8		
Overall Classification = 72.3%, Kappa Coefficient = 0.71								
Accuracy assessment of the Landsat 5 TM 2007								
Classification Data	Open Water	33	3	0	3	0	39	84.6
	Wet Grassland	1	51	1	0	2	55	92.7
	Forest and Shrubs	0	2	27	5	0	34	79.4
	Agriculture	7		0	43	1	51	84.3
	Bare	0	1	6	0	31	38	81.6
Total		41	57	34	51	34	217	
Producer's Accuracy (%)		80.5	89.5	79.4	84.3	91.2		
Overall Classification = 85.3%, Kappa Coefficient = 0.82								
Accuracy assessment of the Landsat 8 OLI-TIRS 2017								
Classification Data	Open Water	34	6	3	3	4	50	68
	Wet Grassland	1	57	7	3	1	69	82.6
	Forest and Shrubs	6	7	33	0	5	51	64.7
	Agriculture	3	3	2	41	3	52	78.8
	Bare	8	0	2	3	27	40	67.5
Total		52	73	47	50	40	262	
Producer's Accuracy (%)		65.4	78.1	70.2	82	67.5		
Overall Classification = 73.3%, Kappa Coefficient = 0.72								